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Next Generation 4-D Distributed Modeling and Visualization of Battlefield

ABSTRACT

Gaining a detailed tactical picture of the modern battle-space is vital to the success of any military operation. This picture is used to direct the movement of assets and material over rugged terrain during day and night in uncertain weather conditions, taking account of possible enemy locations and activity. To provide a timely and accurate picture of the battle-space, most modern command operations centers have access to a multitude of systems which provide information from many different sources including eye witness reports, aerial photographs, sonar, radar, synthetic aperture radar, multi-spectral imaging, hyper spectral imaging, foliage penetration radar, electro-optic, infrared and moving target imaging data. These disparate and sometimes conflicting sources must be combined together in a timely and accurate fashion to provide an overall view of the battle-space that is clear, concise, coherent, complete and accurate.

In this MURI project, we have developed algorithms and systems to address the above problems as they relate to 3D and 4D modeling and visualization of battle-space. They include: 3D modeling of urban and suburban environments, updating the models, tracking and registration, visualizing and rendering large scale 3D models, mobile situational visualization, 4D modeling of dynamic scenes including the temporal dimension, augmented virtual environments merging stationary or temporal video data with 3D models, uncertainty processing and visualization, information fusion, and decision making under uncertainty. In doing so, we have developed the first fully automated 3D modeling system for urban environments capable of generating photorealistic views for walk-through, drive through and fly-throughs.

List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

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1. STATEMENT OF THE PROBLEM STUDIED

Gaining a detailed tactical picture of the modern battle-space is vital to the success of any military operation. This picture is used to direct the movement of assets and material over rugged terrain during day and night, in uncertain weather conditions, taking account of possible enemy locations and activity. To provide a timely and accurate picture of the battlespace, most modern command operations centers (COC) have access to a multitude of systems which provide information from many different sources including eye witness reports, aerial photographs, sonar, radar, synthetic aperture radar (SAR), multi-spectral imaging (MSI), hyper spectral imaging (HSI), foliage penetration radar (FOPEN), electro-optic (EO), infrared (IR) and moving target imaging (MTI) data. These disparate and sometimes conflicting sources must be combined together to present the tactical view. However, the quantities of information are sufficiently large that it is impossible for an individual to be able to collect and comprehend all the information. Typically, each information source is analyzed individually by a specially trained technician. Even then, fusing these disparate data sources is difficult. The goal is to provide an overall view of the battle-space that is clear, concise, coherent, complete and accurate. However, the effectiveness of such a view is determined by its usability. If the picture contained all the information that had been collected, the commanders would be overloaded by the quantity of information.

Historically, most tactical decision makings were performed on a sand table, i.e. a box filled with sand shaped to replicate the battlespace terrain. Commanders moved around small physical replicas of battlefield objects to visualize battlefield situations. Currently, these same operations are carried out using detailed paper maps and acetate overlays. These maps and overlays can take several hours to print, distribute and update. To speed up the visualization process, the joint Maritime Command Information System (JMCIS), a widely fielded military information system including a visualization module was developed. Although JMCIS is extremely powerful and flexible, it has two significant problems for battlefield visualization: clutter and the loss of three dimensional information. Visualization difficulties can be reduced by replacing the two dimensional plan view by a three dimensional display, as is done in the virtual environment for battlefield visualization called Dragon that is implemented on a Responsive Workbench at Naval Research Labs. Essentially, the Workbench is an electronic 3D sand table. Applications in which several users collaborate around a workspace such as a table are excellent candidates for the workbench; however, the Workbench imagery is only correct for one or two observers, whose 3D viewpoints are correctly tracked. Other non-tracked users can observe the scene as well, but their perception is distorted.

While the Dragon system presents a leap forward as compared to sand tables, maps and overlays and two dimensional visualization systems, it can be improved in several ways: First and foremost, the workbench is most useful in applications where several users collaborate around a workspace, such as a table. As such it is not suitable for the mobile soldier, or pilot, or other military personnel that cannot possibly carry a workbench and are thus limited to lightweight Personal Digital Assistants (PDA) or Head Mounted Displays (HMD) for 3D display purposes. For example, mobile PDA or HMD displays

can provide useful information from both a user's (first-person) perspective or an aerial perspective: different presentation issues relate to these two views of the same information.

Second, the workbench can be enhanced with augmented reality techniques whereby actual imagery and video from the battlespace can be registered with computer generated terrain data stored in geospatial databases and displayed as the virtual environments. In a mobile scenario, this can help the mobile individuals identify where they are located, and visualize where they are heading. For instance, a soldier in a battlefield might use the system to find out what lies beyond the large hill he sees in front of him. In addition to providing valuable navigation information to the mobile military personnel, the captured imagery/video from individual soldiers in the field can be used to update the centralized or decentralized visualization databases. An important question to answer in this context is the extent to which mobile users need to update their visualization databases based on each other's visual imagery. Generating and updating visualization databases using synthetic data such as maps and elevation data, or real data such as images and video, in an automatic, yet accurate and fast way is an important element of our research agenda.

Third, a battlefield necessarily deals with uncertainty, and it is necessary to determine ways to represent and encode the confidence level that exists for each piece of battlefield data. For example, as the last reported position of an entity ages, the uncertainty of where the entity is currently located grows. In a broader sense, uncertainty can either result from sensor errors or processing algorithms such as image understanding and analysis and target recognition algorithms. An important challenge is to present the level of uncertainty associated with each object in the virtual scene in a visually intuitive way without cluttering or resulting in information overload. Uncertainty can also be used to prioritize the information that needs to be presented to the users.

Fourth, time must also become a part of battlefield visualization system. This might be used to play back the previous 24 hours or to store and review the plans for the upcoming 24 hours. This necessitates the generation of 4D models, three determining space and the fourth dimension giving time. Fast, accurate and automatic model generation based on synthetic data such as maps and elevation data as well as real imagery is an important research topic.

Fifth, distributed computing is the direction in which all military systems are moving. This includes remote person-to-person collaboration as well as distributing the computing across multiple platforms.

Based on the above requirements, we have investigated a distributed, database system for battlefield visualization, tailored to the needs of future mobile military personnel. This database incorporates and presents uncertainty associated with objects in the virtual scene, is four dimensional, and is initially constructed by registering sensor imagery to ground control points and reference imagery, with the additional input of maps and elevation data. The resulting 4-D model provides the scene context for interaction, interpretation, and the visualization needs of the users. The users not only extract and

visualize information from this system, but also contribute to updating it. In doing so, 4D model updates are placed into special geo-referenced data structure necessary for real time visual navigation of very large data collections; time is treated on the same footing as spatial dimensions so that one can navigate through time as well as space or jump from time to time for accurately geo-located data.

In what follows, we provide highlights of our research results for this MURI project; these include (a) automatic 3D modeling of urban environments (b) real time sensor data fusion with 3D models and visualization (c) mobile augmented battlefield visualization (d) quantifying and visualizing uncertainty (d) decision making with uncertain image and sensor data. In what follows we elaborate on each one of these in detail.

2. SUMMARY OF THE MOST IMPORTANT RESULTS

2.1 Results in 3D Modeling

2.1.1 Automated 3D City Modeling

Many current and future military operations are likely to take place in cities, requiring the U.S. military to be prepared to engage in operations in urban areas. As such, a major key to success in such missions is the ability to model real-world urban areas accurately and effectively, so as to support US military mission planning, operations, and training. This requires urban terrain mapping, interrogation, and visualization capabilities, together with frequent update processing. In addition to military applications, three dimensional urban models are used in civilian applications such as urban planning, virtual reality, gaming and entertainment industries, and simulation of the propagation of radio waves for the cell phone industry.

Acquisition of 3D city models has traditionally been difficult and time consuming. As such, large scale models typically take months to create, and usually require significant manual intervention [ChaShe98]. This process is not only prohibitively expensive, but also is unsuitable in applications where a 3D snapshot of a city is needed within a short time, e.g. for disaster management or for monitoring changes over time.

There exist a variety of approaches to creating 3D models of cities from an airborne view via remote sensing. One approach is to use aerial images in stereo vision algorithms [Frere98]. In recent years, advances in resolution and accuracy of airborne laser scanners have also rendered them suitable for the generation of 3D models [Brenner2001,Maas2001]. Although these methods can be reasonably fast, the resulting resolution of the models is not high, and without manual intervention, the resulting accuracy is also poor. Specifically, they lack the level of detail that is required for realistic virtual walk-throughs or drive-throughs needed in military applications.

Previous work on acquiring detailed building models from a ground-level view has been limited to one or few buildings: Debevec et al. proposes to reconstruct a building based on few camera images in a semi-automated way [debevec]. Stamos and Allen use a 3D

laser scanner [stamos], and Thrun et al. [thrun] and Hahnel et al. [hahnel] use 2D laser scanners mounted on a mobile robot to achieve complete automation, but the time required for data acquisition of an entire city is prohibitively large; Antone and Teller [antone] propose an approach based on high-resolution half-spherical images, but data has to be acquired in a stop-and-go fashion.

Over the past 6 years, under this MURI program, the Berkeley team has developed data acquisition and processing techniques for fast, automated, photorealistic, 3D modeling of urban terrain that can be used for virtual walk-throughs, drive-throughs, and fly-throughs [AZ1,AZ2,AZ3,AZ4,AZ5,AZ6,AZ7,AZ8,AZ9,AZ10,AZ11,AZ12,AZ13]. Our approach uses laser and camera data both at the ground and aerial level, and consists of several steps: (a) accurate localization of the ground acquisition vehicle; (b) processing of the ground based laser and camera imagery in order to arrive at accurate 3D models of the facades of buildings; (c) acquisition and processing of airborne laser and camera imagery in order to arrive at accurate 3D models of rooftops; (d) registration of the data from ground and aerial data with respect to each other; (e) merging of the ground and aerial models in order to arrive at a complete model of an urban environments; the flow diagram for our overall modeling approach is shown in Figure 1.

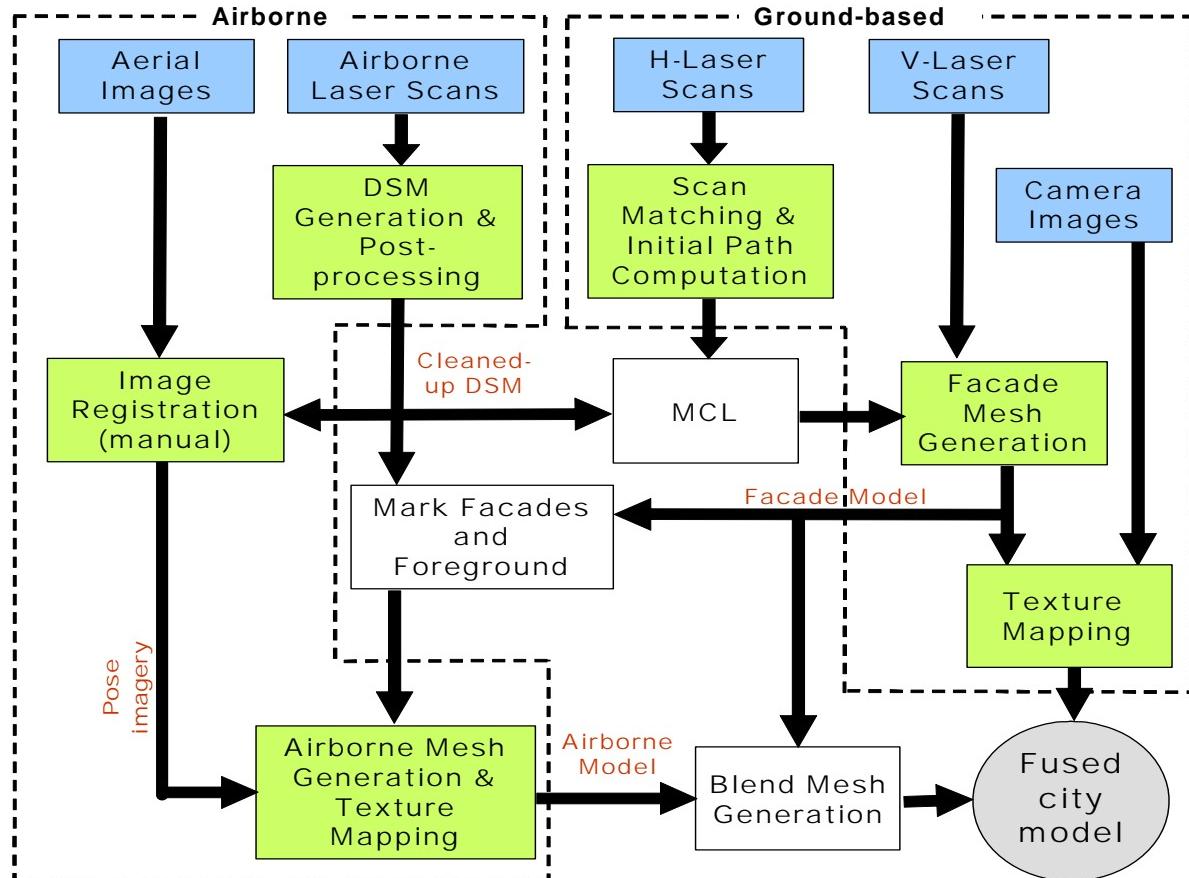


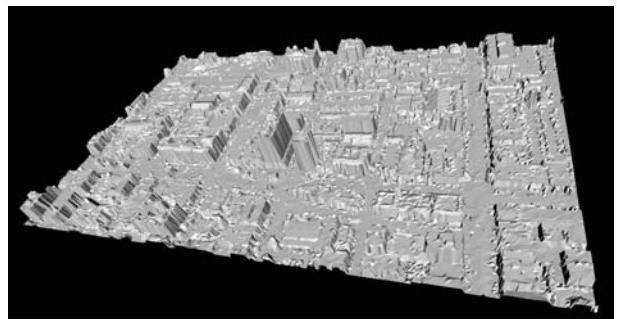
Figure 1: Data flow diagram of our modeling approach. Airborne modeling steps are highlighted in green, ground-based modeling steps in yellow, and model fusion steps in white.

Our ground based data acquisition system consisted of two fast, inexpensive 2D laser scanners, one horizontal, and one vertical, and a digital camera. This data acquisition system is mounted on a truck moving at a normal speed on public roads, collecting data to be processed offline. This approach has the advantage that data can be acquired continuously, rather than in a stop-and-go fashion, and is therefore much faster than existing methods based on 3D scanners. The basic idea is to stack the vertical laser scans acquired over time next to each other at proper positions in order to arrive at a faithful reconstruction of the building facades. As such, it is necessary to determine the pose of successive laser scans and camera images in a global coordinate system with centimeter and sub-degree accuracy. We have accomplished this by computing relative position changes via matching successive horizontal laser scans against each other [AZ2]. Furthermore, we have developed a novel particle filtering based method to correct accumulating pose uncertainty by using airborne data such as aerial photo or a digital surface model (DSM) as a reference [AZ13]. An inherent advantage of this approach is that it automatically registers ground level laser scans and camera images with airborne data, facilitating subsequent fusion of the aerial and ground models in later steps [AZ3].

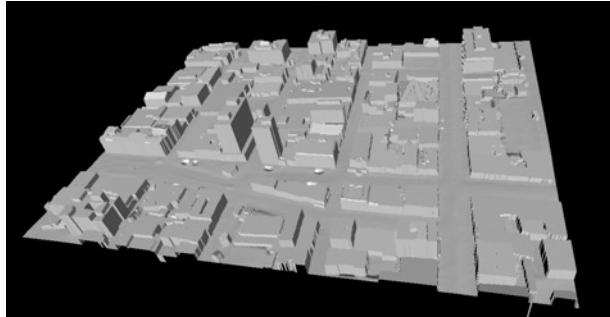
Once the ground based vehicle is accurately localized, it is possible to stack successive vertical laser scans to construct a structured point cloud of the facades of the buildings. As there are many erroneous scan points, e.g. due to glass surfaces and foreground objects partially occluding the desired buildings, the generation of a facade mesh is not straightforward. Specifically, a simple triangulation of the raw scan points by connecting neighboring points whose distance is below a threshold value does not result in an acceptable reconstruction of the street scenery. In [AZ1], we have developed a class of data processing algorithms to create visually appealing facade models from the ground based data by first converting our triangulated 3D model into a 2.5 dimensional depth map, and introducing a representation based on multiple depth layers of the street scenery. Each depth layer is a scan grid, and the scan points of the original grid are assigned to exactly one of the layers. If at a certain grid location there is a point in a foreground layer, this location is empty in all layers behind it, and needs to be filled in. In practice, we have found it to be sufficient to generate only two layers, namely a foreground and a background layer. We then apply depth based histogram analysis to separate foreground objects such as trees, cars, pedestrians, telephone poles, from those of the background, i.e. building facades. Subsequently, erroneous scan points in the background layer are detected and removed, the occluding foreground layer is segmented into objects, and occlusion holes resulting from such objects are filled using a RANSAC based plane fitting algorithm [AZ1].

In [AZ3], we develop a series of processing steps for airborne laser data consisting of (a) re-sampling and interpolation of the raw laser data; (b) segmentation of the rooftops based on depth discontinuity; (c) removing small segments such as ventilation ducts; (d) hole filling by extrapolation of nearby planar segments; (e) finding polygonal approximation for segment perimeter based on RANSAC, and (f) straightening of the edges; Figures 2(a) and 2(b) show the triangulation of the airborne Berkeley data and its postprocessed version respectively. As seen, the above processing steps result in a

dramatic improvement in the visual quality of the model. Figure 2(c) shows the texture mapped version of the processed DSM via airborne top down imagery.



(a)



(b)



(c)

Figure 2: Airborne model. (a) DSM directly triangulated, (b) triangulated after postprocessing, (c) model texture-mapped.

Once the airborne and ground based models have been generated, they need to be combined to generate a complete model. Since the two models have been registered with respect to each other in the ground vehicle localization step described earlier, no further

registration is needed. However, merging of the two models is still a particularly challenging task since the resolutions of the two models are vastly different, with the resolution of the facade model being about 10 centimeters, and that of the airborne model around half a meter. To enable interactive rendering, the two models need to fit together even if their parts are at different levels of detail or resolutions. To address this problem, we have developed a “blend mesh” approach to fill in the gaps that inevitably exist between the two models [AZ3]. An example of walk-through and fly through views of the model for a portion of University Avenue in downtown Berkeley as seen from the ground level is shown in Figure 3. As seen, the model is quite photo-realistic, and can be used for virtual navigation through streets of Berkeley in walk/drive/fly-through modes.

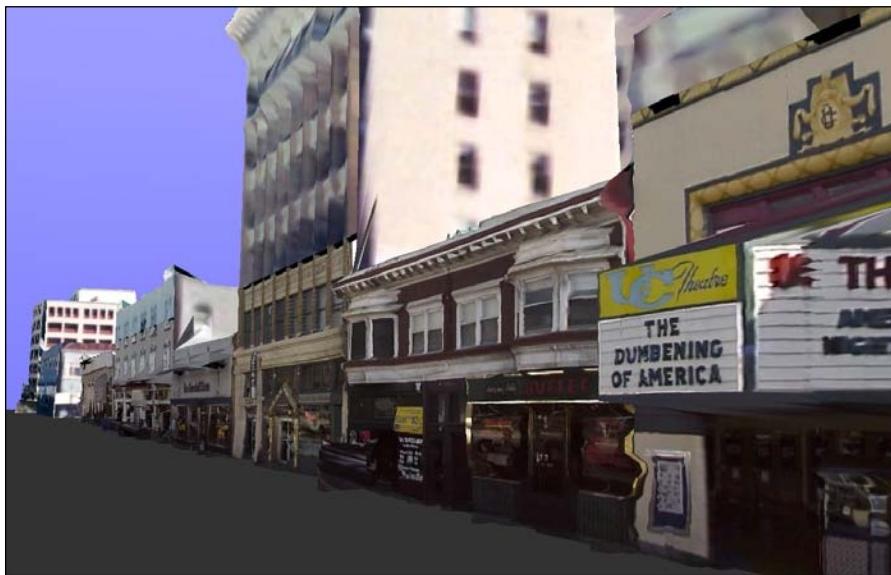


Figure 3: Examples of Walkthrough and Fly-through for downtown Berkeley

Resulting 3D models of downtown Berkeley can be downloaded from:

<http://www-video.eecs.berkeley.edu/~frueh/3d/index.html>

In addition, a Quicktime video of interactive walk/drive/fly through for downtown Berkeley can be downloaded from:

<http://www-video.eecs.berkeley.edu/~avz/down11.mov>

In the past two years, we have further extended our basic modeling approach in several directions:

2.1.2 Extension to suburban and residential areas with trees

We have developed an approach to detecting trees in registered aerial image and range data obtained via LiDAR [AZ12,AZ13]. Representing the trees in 3D models is problematic because the data are usually too sparsely sampled in tree regions to create an accurate 3-D model of the trees. Furthermore, including the tree data points interferes with the polygonization step of the building roof top models. Therefore, it is advantageous to detect and remove points that represent trees in both LiDAR and aerial imagery. We have developed a two-step method for tree detection consisting of segmentation followed by classification. The segmentation is done using a simple region growing algorithm using weighted features from aerial image and LiDAR, such as height, texture map, height variation, and normal vector estimates. The weights for the features are determined using a learning method on random walks. The classification is done using weighted support vector machines (SVM), allowing us to control the misclassification rate. The overall problem is formulated as a binary detection problem, and the results presented as receiver operating characteristic curves are shown to validate our approach. As shown in Figure 4, this method is capable of segmenting and classifying trees in urban environments.

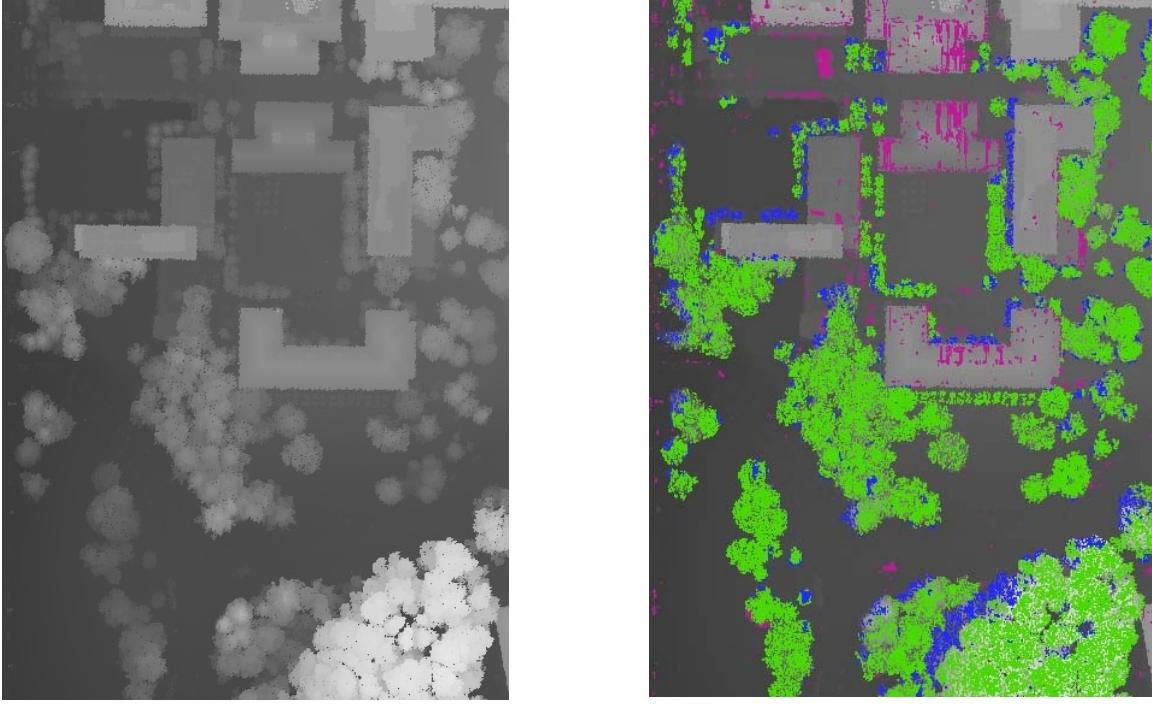


Figure 4: Example of segmentation of UC Berkeley campus data; green denotes correctly classified trees; pink shows non-trees incorrectly classified as trees; blue denotes trees incorrectly classified as non-trees.

2.1.3 Semi-Automatic Modeling of Cities

The USC team has developed a complete modeling system that can extract and refine complex building structures with irregular shapes and surfaces in a semi-automated way. The global building footprints and roof data provided by the LiDAR reconstruction is used to determine the geo-locations of buildings and isolate them from surrounding terrain. Based on the shape of a building roof (flat-roof, slope-roof, dome-roof, gable-roof, etc.), we divide a complex building into several basic building primitives (including the standard CG primitives such as plane, cube, wedge, polyhedron, cylinder and sphere, and high-order surface primitives such as superquadrics) and model them using a parametric representation. As the models from constructive solid geometry allow the composition of complex models from basic primitives that are represented as parametric models, our approach is quite general. Also, as the type of primitive is not limited, may contain objects with curved surfaces, so the flexibility of model combinations is very high, hence we can model a range of complex buildings with irregular shapes and surfaces by combining appropriate geometry primitives and fitting strategies.

This system is semi-automatic in that it requires user interaction to select the building section and associated group type. Once the user input is provided, the system automatically performs the processing including boundary segmentation, primitive fitting, model refinement, and optimization to complete the building model. Our system

also provides a range of editing tools, allowing users to further refine the models or obtain a specific representation quickly. The system has been tested using a range of different building structures. Figure shows the result of modeling entire USC campus and surrounding University Park area including the Coliseum, LA Arena, museums, and gardens.

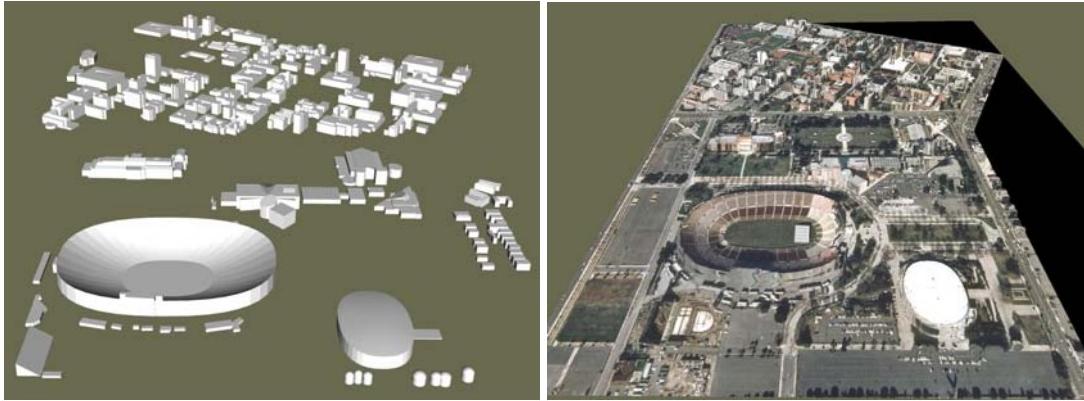


Figure 5 : Complete refined models of USC campus and surrounding University Park area (left). An aerial photograph is projected on the models heightening the realism of models (right). The model was created in two days using the developed system

2.2 Results on 4D capture and Modeling

2.2.1 Augmented Virtual Environment (AVE)

Dynamic scene analysis and object extraction are traditional problems in computer vision. We have introduced the concept of *Augmented Virtual Environment (AVE)* as the framework for incorporating our proposed model/image/video/data fusion techniques and algorithms. The AVE is a novel and comprehensive approach to data fusion, analysis, and visualization that incorporates and presents all the sensors, abstract data, objects, and scenes models within a common context to produce a concise, coherent, and non-conflicting representation for time-space interpretation of real world activity. The AVE framework is particularly suited to addressing the difficult problem posed by multiple video sources. In an AVE system, image sensors are modeled as “virtual projectors” (VPs) that have the same imaging parameters as the sensors.

The overall approach is the fusion of video streams in the context of 3D models. In order to achieve that, several problems had to be addressed including: rapid 3D modeling of the site in order to provide the context for video fusion; efficient encoding/decoding and transfer of video into the host computer; real-time texture projection onto 3D models; and texture management for scalable performance to 100’s of cameras. Sub-barriers within the problem of rapid and accurate modeling of terrain and structures include data fusion and integration of multiple data sources (images and LiDAR) as well as integrated automated tools for rapid processing of data.

Our research activities resulted in the development of methods and algorithms for scalable video acquisition and texture management. These new algorithms are now a part of the AVE system, automatically managing the compression quality, video frame rate, and video image size of each video stream so that a workload ceiling on the AVE system is never exceeded. A limit on the system workload means that real-time rendering and interaction with the user is maintained for an arbitrarily high number of camera video streams.

Encoding/decoding of video Initial efforts to move video into a computer and apply it as a dynamic texture proved to be cumbersome and slow. The movement of large volumes of data exceeded the limits of computer systems. By careful testing, and engineering, we leveraged the available high performance subsystems in current computers and graphics cards, as well as the emerging commercial trend for video-over-IP products. Multithreading and multiple CPU or CPU Core systems allow for efficient utilization and parallel decoding of video. High bandwidth networks (Gigabit Ethernet) provide commercial solutions to video routing. Optimized JPEG and MPEG software decoders provide high performance decoding of multiple video streams.

Real-time texture projection onto 3D models Once decoded video is available in a host computer, its projection onto a 3D model requires high bandwidth data transfer and high throughput graphics rendering with textures. We optimize our algorithms to make the most of the high-performance AGP and PCIE bandwidth to graphics cards and their high rendering performance. We developed visibility culling and multiscale texturing algorithms to maintain high throughput under all viewing conditions. We developed parallel shader GPU programs to accelerate the texture projection processing.

Texture management for scalable performance to 100's of cameras We developed methods and algorithms for scalable video acquisition and texture management. These algorithms automatically manage the compression quality, video frame rate, and video image size of each video stream so that a workload ceiling on the AVE system is never exceeded. A limit on the system workload means that real-time rendering and interaction with the user is maintained for an arbitrarily high number of camera video streams.

2.2.2 Dynamic Scene Capturing System

The UC Berkeley team has started to investigate a new approach for capturing dynamic scenes such as a basketball game or soldiers fighting. Our goal is to acquire both 3D geometry and visual appearance of a scene over time, and thus essentially record a 4D movie which could be viewed afterwards from any arbitrary position. Our approach utilizes a video camera, an infrared (IR) camera, a pattern of vertical IR light stripes, and a 2D IR line laser with a rotating mirror in a setup as shown in Figure 6*Figure(a)*. We use structured IR light in order to avoid interfering with or disturbing the moving persons or objects.

An invisible static line pattern of equally spaced vertical lines is projected onto the scene with the IR line projector, and this line pattern is recorded from a different position at 15

Hz frame rate with the infrared camera. Due to the different viewpoint, the projected lines are curved in the images according to the shape of the objects, and we track each of them and obtain a set of curved lines. If we manage to identify the IR light plane equation for each curved line in the IR image, we can reconstruct the depth of the objects along the lines based on triangulation. However, identifying the corresponding IR light plane is a non-trivial problem; in previous work, solutions such as line coding or time multiplexing have been proposed, which are not applicable for IR systems and dynamic scenes, respectively. In our approach, we attempt to solve this identification problem via a horizontal IR line laser.

Using a rotating mirror, we sweep the IR laser line vertically over the scene at a low frame rate, e.g. 1Hz. Since this is the only horizontal IR line in the image, it is easy to identify. Knowing the angle of the rotating mirror, we can compute the depth accurately along this line. For the vertical lines which intersect with this laser line, we can compute the IR light plane equation by using the 3D coordinates of the intersection point, the center-of-projection of the IR light projector, and the verticality of the light planes (intra-frame line tracking). For vertical lines that do not intersect with the horizontal line, we determine vertical lines in the previous frame which were close, and utilize their plane equation; this is possible because the motion between 2 frames, i.e. within 66 ms, is limited. Since the horizontal line sweeps continuously across the scene, the plane equation for every line segment is identified at some point; by tracking lines across the frames (inter-frame line tracking), we can pass on the plane equation from one frame to the next one.

Our results on this work are preliminary but promising. Figure 6(b) shows a frame from the IR video of our acquisition system, and Figure 6(c) the reconstructed depth of the moving object.



Figure 6: Dynamic scene capturing: (a) setup, (b) IR camera view with projected vertical stripes and the horizontal laser line, (c) reconstructed depth.

A video of interactive rendering of a time varying human object in a room can be downloaded from:

<http://www-video.eecs.berkeley.edu/~avz/NewDynSceneMovie.avi>

2.3. Results on Mobile Situational Visualization

Accomplishments of this MURI program on mobile situational visualization include:

- Development of a testbed for mobile augmented battlefield visualization.
- Creation, development, and evaluation of “mobile situational visualization”.
 - Development of a mobile prototype including a command center, server architecture, and connected, collaborating mobile participants with GPS, orientation tracking, and shared annotations.
 - Testing and evaluation of the mobile environment with tracking scenarios to show capabilities and effectiveness.
- In conjunction with Syracuse University, added dynamic decision support to mobile situational visualization so that paths could be chosen under the placement of moving, changing risks. Paths were chosen in a trade-off of lowered risk versus shorter distance.
- Developed new simplification methods for detailed 3D building models so that they could be rendered quickly with appropriate appearance characteristics.
 - Punctuated simplification method for producing significant, even extreme, simplifications of manmade models while preserving shape.
 - Appearance-preserving level of detail method for producing continuous LOD simplifications that applies an error metric to both geometry and appearance (e.g., textures).
- Created a novel approach that uses the principals of urban legibility to determine levels of abstraction for completely free navigation of massive urban models (with hundreds of thousands of buildings). With this approach skylines and neighborhoods are simplified in such a way that the overall structure of the city remains legible and understandable while close-up details are retained.
- Developed methods to automatically generate dense urban models. A variety of sources including insurance databases, LIDAR scans, topographic data, and existing models are combined automatically. The resulting urban model has both generic and specific structures; the former have accurate footprints, orientation, locations, and heights. Generic roof and façade textures are automatically generated. Using these methods, we generated extensive urban models for both Atlanta and Charlotte. The latter model has in excess of 370,000 buildings.
- Development of new methods to automatically extract tree and shrub footprints from ortho-rectified color aerial images. Tree and shrub models can then be generated from these with heights generate either procedurally from an analysis of the tree width or directly from LIDAR data.
- Development of new multimodal interfaces for mobile situational visualization. Interfaces include gesture tracking using a chest pendant with camera, hand orientation tracking, and tablet-based sketch input.
- Presented mobile situational visualization and its relation to homeland security at invited talks at a special session of the AAAS meeting on the National Visualization and Analytics Center (February, 2005), at AppliedVis 2005 (May, 2005), and at an invited presentation for the DHS Regional Visualization and Analytics Centers (January, 2006).

- Using work in urban terrain analysis begun under this MURI as a foundation, began work on a project sponsored by ARO for eye-point dependent models applied to terrain analysis and applications such as line-of-sight.
- Based on discussions with the program manager at DARPA IXO, we were encouraged to submit a proposal on mobile situational visualization (in conjunction with Syracuse University). Although the proposal was not funded, we are continuing to explore these possibilities with DARPA.
- We presented our mobile system and visualization capabilities to many individuals in state and national government and also to the military. The system was also a key presentation during the Georgia Tech Homeland Defense Workshop. The system is being used as part of the Sarnoff Raptor system, which is deployed to the Army and other military entities. In addition our visualization system is being used as part of the Raptor system at Scott Air Force Base.
- VGIS, which is the foundation for our mobile visualization system, was licensed by Sarnoff Corp. It is being used in a system that provides an integrated picture of aircraft operations and ground movements.
- Our system was presented as part of a mobile emergency response application to President Bush and Governor Tom Ridge, at that time head of DHS. The presentation was part of an extensive exercise for emergency response in an urban setting to a terrorist attack, in this case the release of sarin gas inside and outside a large building in the city.
- Situational visualization and mobile battlefield applications were presented to Paul Dumanoir and Pamela Woodard, program directors at STRICOM in Orlando.
- Our systems have been used in a variety of exercises in support of the Marines (in collaboration with NRL)—we have done some work in developing full 3D model, trees, etc. Displayed results on laptop with GIS positioning. Integrated mesoscale weather simulation (MM5).

2.4 Results on Decision Making with Uncertainty

This research thrust addressed the development of methodologies for handling uncertainty in space and time-conscious battlefield scenarios. Analyses and algorithms were developed to address dynamically changing environments to assist detection, tracking and visualization tasks. The highlights of this work are summarized below.

2.4.1 Temporal Uncertainty Reasoning:

We developed an approach based on Bayesian networks for time-sensitive belief propagation in the context of dynamically changing environments, where the relevance of observations decays with time. A compact and efficient continuous-time representation is used, unlike the dominant “time-slice” approach predominant in the literature. Conditional probabilities associated with edges in the networks depend on time in two ways: the exact timestamp associated with individual nodes in the network, and the time delays between observations and other hypotheses associated with nodes. The network propagation model has been implemented along with a visualized battlefield tracking

application where uncertain observations of tracked entities are made using multiple sensors.

2.4.2 Decision Fusion in a Large WSN:

For a wireless sensor network (WSN) deployed in the battlefield with a random number of sensors, we have proposed a decision fusion rule that uses the total number of detections reported by local sensors as a statistic for hypothesis testing. We assume that the signal power attenuates as a function of the distance from the target, the number of sensors follows a Poisson distribution, and the locations of sensors follow a uniform distribution within the region of interest (ROI). Both analytical and simulation results for system-level detection performance have been provided. This fusion rule can achieve a very good system-level detection performance even at very low signal to noise ratio (SNR), as long as the average number of sensors is sufficiently large. For all the different system parameters we have explored, the proposed fusion rule is equivalent to the optimal fusion rule, which requires much more prior information. The problem of designing an optimum local sensor-level threshold has been investigated. For various system parameters, the optimal thresholds have been found numerically by maximizing the deflection coefficient. Guidelines on selecting the optimal local sensor-level threshold have also been provided.

2.4.3 Fusion of Decisions Corrupted by Fading Channels:

We have investigated the decision fusion problem for decisions transmitted over noisy and fading wireless channels. In a conventional distributed detection system, it is often assumed that the decisions sent from local sensors are perfectly recovered at the fusion center. However, because of the harsh and hostile battlefield environment, the power of transmitted signal should be kept to a minimum to attain a low probability of intercept/detection (LPI/LPD). As a result, for a WSN deployed in a battlefield, the transmitted information has to endure both channel fading and noise/interference, since error protection via channel coding and increased transmitter power may not be desirable due to limited resources. We have developed a decision fusion rule that intelligently deals with channel fading, and that provides robust detection performance in the presence of channel noise and channel fading.

2.4.4 Temporal Staggering for Target Tracking:

Several practical battlefield target tracking scenarios require the periodic collection of uncertain information from multiple sensors, with different measurement noise variances. Decisions need to be made regarding the optimal strategies for collecting data over time from different sensors. We have studied the effects of temporally staggered sensors on system performance, and evaluated them by comparison to synchronous sensors. Optimal staggering patterns have been found numerically in some simulations. Practical guidelines on selecting optimal staggering patterns have been obtained for different target tracking scenarios.

2.4.5 Distributed Sequential Detection:

We have considered the problem of distributed sequential detection in the presence of communication constraints for a sensor network. The observations available at each sensor are first compressed to multi-bit sensor decisions and sent to the fusion center. At the fusion center, a sequential data fusion scheme is implemented in order to reach a global decision. An algorithm has been developed for optimal bandwidth distribution among sensors under a fixed bandwidth constraint. Under symmetry and conditional independence assumptions, the algorithm can be simplified substantially: the cooperative quantizer design algorithm reduces to independent quantizer design. The case when communication bandwidth is the only constraint has also been considered.

2.4.6 Activity Change Recognition:

Visualization in dynamic battlefield environments, using information from multiple sensors observing multiple locations, necessitates automatically focusing attention on the regions of interest where important changes have occurred in the activities of individuals being monitored. We have addressed this problem, developing a new Control Charts approach for activity change recognition using human activity data from video image sequences.

2.4.7 Heterogeneous Sensor Data Fusion:

In battlefield surveillance-related applications, asynchronously arriving data from heterogeneous sensors needs to be combined effectively in order to draw some inferences that cannot be drawn from individual data streams by themselves. This problem is particularly difficult when the data streams are incommensurate and substantially different. We have addressed this problem by developing a heterogeneous sensor fusion methodology with multiple sensor-specific data processing pipelines that send information asynchronously to the decision-maker, which bases its current conclusions on all the data received thus far from various data streams. We have applied this approach to the task of fusing audio and video data streams, classifying entities in the environment and detecting the activities of multiple individuals, using neural networks and fuzzy rules for classification decisions. Situation-specific domain knowledge such as information regarding the positions of certain scene landmarks such as position of cars etc, helps to provide a richer understanding of the scene context and ability to spot specific events.

2.4.8 Distributed Particle Filters:

Noisy sensor measurements result in detection failures and false alarms when tracking numerous indistinguishable targets appearing at random in space and time. We have developed distributed particle filter techniques to address these problems, improving the accuracy of non-linear/non-Gaussian tracking problems in a multi-sensor environment, where the (Extended) Kalman Filter approach often fails. To save the communication bandwidth, we introduce a modified Expectation Maximization algorithm to compress

the local tracking information before sending it to the fusion center. A corresponding fusion approach is also introduced to fuse the information collected from each sensor and generate the sub-optimal estimation about the moving targets. We have also addressed the maximization of network lifetime for target tracking by intelligently activating the most appropriate sensors and deactivating others to save energy.

2.4.9 Vehicle Movement Uncertainty Visualization:

In collaboration with MURI team-members from Univ. of California at Santa Cruz, we have developed techniques for the visualization of uncertainty associated with the locations of objects such as vehicles moving on road segments. An important aspect of this work is that the associated uncertainty changes with space and time, generally depending on the reliability of the sensed information and the timestamps of observations.

2.4.10 Personnel movement:

An important scenario for the application of various uncertainty reasoning and visualization algorithms is the task of planning personnel movements in the battlefield, with uncertain information arriving over time from multiple spatially distributed sensors or observers. We have addressed this task, developing algorithms for fast computation of near-optimal paths, updated rapidly when new information arrives after personnel movement has been initiated. We have developed a new hierarchical path planning algorithm (HIPLA) for fast computation of near optimal paths for such applications, which incorporates the dynamic aspect as an integral part of the path planning model. When the risk estimates associated with nodes change with time after personnel have started traversing a path, HIPLA computes a new sub-path from their current location to destination nodes, reusing the previously computed risk estimates for the unaffected portions of the graph, saving significant computational time as opposed to re-computation of the whole path in the original graph. Simulations, carried out with graphs containing upto 19,600 nodes, showed that HIPLA outperforms two state-of-the-art algorithms viz., Shortest path algorithm (SPA) and Dijkstra's algorithm with pruning (DP), achieving near-optimal solutions with substantially less computational effort. For personnel movement scenarios where multiple objectives need to be optimized (e.g., cost, time, risk to personnel, and utility associated with reaching destination), we have developed a new multi-objective evolutionary algorithm (EMOCA) and shown that it outperforms state-of-the-art algorithms such as NSGA-II. We have collaborated with MURI team-members (from Georgia Tech./Univ. of N. Carolina) to apply these algorithms to experiments involving the actual movements of individuals (being tracked) in a University Campus.

2.5 Results on Uncertainty Visualization

Our vision is that all information and decisions should include a measure of confidence. This measure of confidence, or uncertainty, may be encoded directly with the visualization, or it may be provided to the user in another form. In summary, we have addressed the issue of credibility in visualizations and decision-making processes

emerging from a mobile augmented battlespace visualization system. Our efforts in this area include the following contributions.

2.5.1 Computation and Visualization of Uncertainty for Terrains while Preserving Topological Features within the GIS context

Here we include a brief summary of our efforts on computing and visualizing uncertainty related to the compression of large terrain data sets. We present an algorithm for compressing terrain data that preserves topology. We use a decimation algorithm that simplifies the given data set using hierarchical clustering. Topology constraints along with local error metrics are used to ensure topology preserving compression and compute precise error bounds in the compressed data. Earth's mover distance is used as a global metric to compute the degradation in topology as the compression proceeds. Results indicate that one can obtain significant compression with low uncertainty without losing topology information. During the first year of effort, we focused on preserving point features such as high points, low points, or transition points. During the second year of effort, we have extended the results to line features such as isocontours or polyline data that may be relevant in a battlespace scenario. Since global uncertainty computation for preserving line features is very expensive, we have designed an approximate local computation algorithm that works well in practice.

2.5.2 Uncertainty-Driven Target Tracking

We have created visualization of uncertain information associated with target tracking. As a first step, we modeled the uncertainty associated with the location and velocity of targets as probability distributions. We have visualized the uncertain location of the target as a blob, which can be tracked over time. We discuss the algorithmic complexity of the algorithm for uncertainty computation, and ways to improve its performance. Three visualization techniques (galaxy, transparency, and pseudo-color) are developed to represent the resulting probability distribution associated with the particle at a later time. An appropriate time-dependent sampling approach is adopted to make the visualizations more comprehensible to the human viewer. Experiments with different distributions indicate that the resulting visualizations often take the form of recognizable real-world shapes, assisting the user in understanding the nature of a particle's movement. This work was done in collaboration with the Syracuse University.

We investigated an on-line expert algorithm to compute uncertainty of mobile GPS-equipped objects. The algorithm uses the intelligence gathered by experts to decipher a pattern and predict the movements of objects. Depending upon the movement, experts given to the weights are updated in real-time to track the objects.

2.5.3 Embedding Uncertainty within VGIS

This effort required collection, rectification, and registration of various GIS data sets related to Santa Cruz region. We now have many different types of GIS data sets including $\frac{1}{2}$ foot resolution imagery data, elevation data, detailed AUTOCAD drawings,

street maps, and LIDAR data for parts of this region. We have also successfully inserted the imagery and elevation data within the VGIS (Virtual Geographic Information System) developed at the Georgia Institute of Technology. We have been able to visualize uncertainty of mobile objects within the VGIS system. This work is in collaboration with the Georgia Institute of Technology.

2.5.4. Heterogeneous Uncertainty within a GIS Environment

We have investigated and visualized spatio-temporal GPS uncertainty and uncertainty arising due to heterogeneous geo-spatial data. Importance of accurate registration of GPS (Global Positioning System) tracked objects embedded within a GIS (Geographic Information Systems) context has emerged as a critical need in several land, marine, and air navigational systems both for civilian and defense applications. The objective of this work is to measure, model and geo-spatially register the positional accuracy of objects carrying GPS receivers against a GIS background. Although positional accuracy is affected by a number of factors, in this work we have focused on GPS modes (standalone or differential), type of environment (urban or foliage), and type of expected movement of objects. The Ashtech Z-12 sensor is used to collect the data. Linear models are used to estimate the errors associated with the horizontal position information. This error is then visualized upon a 1/2 foot resolution aerial imagery of the UCSC (University of California, Santa Cruz) campus. Estimates of speed and direction errors are used to create visualizations of spatio-temporal uncertainty associated with an object walking through the campus.

GIS data sets acquired using different sensors at different times such as Aerial Lidar data, ground Lidar data, aerial imagery, ground level imagery, Autocad drawings do not register accurately with respect to each other. Sources of error are numerous including sensor noise, geo-spatial registration inaccuracies, shifting of ground over time due to earthquakes, and changing lighting conditions. We compute and display uncertainty in GIS data with a view to create a common consistent view for decision making.

2.5.5 Uncertainty in Cross-Registration of Data acquired at Different Resolutions

Adaptive fusion of new information in a 3D urban scene is an important goal in battlespace visualization. In this work we acquire new image pairs of a scene from closer distances and extract 3D models of successively higher resolutions. We present a new hierarchical approach to register these texture-mapped 3D models with a coarse 3D texture mapped model of an urban scene. First, we use the standard reconstruction algorithm to construct 3D models after establishing 1-1 correspondence between the feature points of two images at same resolution. Next, a subset of these feature points is used to register the higher resolution image with the lower resolution image using a scale-sensitive algorithm. Finally we register and consistently merge the 3D models at different resolutions. We have applied this algorithm successfully for adaptive enhancement of scenes by registering data that differ in scale by a ratio of 1:15. Results indicate that the proposed hierarchical registration technique effectively utilizes the intermediate models to enable the smooth registration of the high resolution models on the coarser models.

2.5.6 Multi-modal Exploration of Uncertainty in Geo-Spatial Environment

We have investigated use of multimodal means to convey uncertainty in an already cluttered and overloaded visualization using expert systems, sound and speech using anticipatory multimodal interfaces. The mobile user is able to view the geo-spatial database interactively and is able to communicate using limited speech vocabulary and receive spoken feedback. Mobile users are able to communicate with each other using wireless. We have also developed anticipatory capabilities to design agents that can learn user profiles to provide proactive feedback to the user.

2.5.7 A Generic Structure-from-Motion Algorithm for Cross-Camera Scenarios

In this work, we first introduce a generic structure-from-motion approach based on a highly generic imaging model, where cameras are modeled as possibly unconstrained sets of sets of projection rays. This approach unifies most existing camera types including pinhole cameras, sensors with radial or more general distortions, and catadioptric cameras (central or non-central). We are able to reconstruct 3D scenes from calibrated images possibly taken by cameras of different types. The question is how accurate is this reconstruction?

We have proposed two approaches for increasing the accuracy of reconstruction obtaining optimal solutions using bundle adjustment. In these approaches, camera motion, calibration and 3D point coordinates are refined simultaneously. The first straightforward approach minimizes distances between 3D points and projection rays. The other more promising approach minimizes re-projection error. However, the general imaging model does not provide analytical expressions for the re-projection error and its derivatives, which are desirable for efficient optimization. Therefore, we proposed to approximate the set of projection rays of a general non-central camera by several clusters of central rays, allowing us to formulate an analytical cost function.

We presented results for two cross-camera scenarios -- a pinhole used together with an omnidirectional camera and a stereo system used with an omnidirectional camera. Using ground-truth and 3D reconstruction results from classical techniques, we show that our generic algorithm is simple, general and accurate for extensions to various cross-camera and multi-camera scenarios.

2.5.8 Ground Classification using Expectation-Maximization

In this work, we classify 3D aerial LiDAR height data into roads, grass, buildings, and trees using a supervised expectation-maximization (EM) algorithm. We have computed and visualized the uncertainty in classification using confusion matrices.

We present an overview of our approach. Since the terrain is highly undulating, we subtract the terrain elevations using digital elevation models (DEMs, easily available from the United States Geological Survey (USGS)) to obtain the height of objects from a

flat level. In addition to this height information, we use height texture (variation in height), intensity (amplitude of lidar response), and multiple (two) returns from lidar to classify the data. Furthermore, we have used luminance (measured in the visible spectrum) from aerial imagery as the fifth feature for classification. We have used mixture of Gaussian models for modeling the training data. Model parameters and the posterior probabilities are estimated using Expectation-Maximization (EM) algorithm.

We experimented with different number of components per model and found that four components per model yield satisfactory results. We have tested the results using leave-one-out as well as random $\frac{1}{n} \times n$ test. Classification results are in the range of 66% -- 84% depending upon the combination of features used that compares very favorably with train-all-test-all results of 85%. Further improvement is achieved using spatial coherence.

2.5.9 Ground Classification using Support Vector Machines (SVM)

We classify 3D aerial lidar scattered height data into buildings, trees, roads, and grass using the Support Vector Machine (SVM) algorithm. We have used five features -- height data, height variation, normal variation, lidar intensity returns, and image intensity -- to classify the data into four classes. We also use only height-derived features -- height, height variation, and normal variation -- to classify the data into three categories -- buildings, trees (high vegetation), and road-grass. We have implemented and experimented with several variations of the SVM algorithm with soft-margin classification to allow for the noise in the data. We have applied our results to classify aerial lidar data collected over approximately 8 square miles. We visualize the classification results along with the associated confidence using a variation of the SVM algorithm producing probabilistic classifications. We observe that the results are stable and robust. We compare the results against the ground truth and obtain higher than 90% accuracy and convincing visual results.

2.5.10 Ground Classification using AdaBoost

We use the AdaBoost algorithm to classify 3D aerial lidar scattered height data into four categories: road, grass, buildings, and trees. To do so we use five features: height, height variation, normal variation, lidar return intensity, and image intensity. We also use only lidar-derived features to organize the data into three classes (the road and grass classes are merged). We apply and test our results using ten regions taken from lidar data collected over an area of approximately eight square miles, obtaining higher than 92% accuracy. We also apply our classifier to our entire dataset, and present visual classification results both with and without uncertainty. We implement and experiment with several variations within the AdaBoost family of algorithms. We observe that our results are robust and stable over all the various tests and algorithmic variations. We also investigate features and values that are most critical in distinguishing between the classes. This insight is important in extending the results from one geographic region to another.

3. BIBLIOGRAPHY

[ChaShe98] T. Chan and J. Shen, "Mathematical models for local non-texture inpaintings", SIAM Journal on Applied Mathematics 2001, p. 1019-1043, vol 62 number 3.

[Frere98] D. Frere, J. Vandekerckhove, T. Moons, and L. Van Gool, "Automatic modeling and 3D reconstruction of urban buildings from aerial imagery", IEEE International Geoscience and Remote Sensing Symposium Proceedings, Seattle, 1998, p.2593-6

[Brenner2001] C. Brenner, N. Haala, and D. Fritsch: "Towards fully automated 3D city model generation", Workshop on Automatic Extraction of Man-Made Objects from Aerial and Space Images III, 2001

[Maas2001] H.-G. Maas, "The suitability of airborne laser scanner data for automatic 3D object reconstruction", Third Int'l Workshop on Automatic Extraction of Man-Made Objects, Ascona, Switzerland, 2001

[debevec] P. E. Debevec, C. J. Taylor, and J. Malik: "Modeling and Rendering Architecture from Photographs", Proc. of ACM SIGGRAPH 1996

[stamos] I. Stamos and P.E. Allen: "3-D model construction using range and image data." Proceedings IEEE Conf. on Computer Vision and Pattern Recognition, Hilton Head Island, 2000, p.531-6

[thrun] S. Thrun: "Probabilistic algorithms in robotics", AI Magazine, vol.21, American Assoc. Artificial Intelligence, Winter 2000, p. 93-109

[hahnel] D. Hahnel, W. Burgard, and S. Thrun: "Learning Compact 3D Models of Indoor and Outdoor Environments with a Mobile Robot", 4th European Workshop on Advanced Mobile Robots (EUROBOT'01), 2001.

[antone] M.E. Antone and S. Teller: "Automatic recovery of relative camera rotations for urban scenes. " Proc. IEEE Conf. on Computer Vision and Pattern Recognition, Hilton Head Island, 2000, p.282-289

[AZ1] C. Frueh, S. Jain, and A. Zakhor, "Data Processing Algorithms for Generating Textured 3D Building Facade Meshes from Laser Scans and Camera Images", International Journal of Computer Vision, Vol. 61 No.2, Feb. 2005, pp. 159-184.

[AZ2] C. Frueh and A. Zakhor, "An Automated Method for Large-Scale, Ground-Based City Model Acquisition" in International Journal of Computer Vision, Vol. 60, No. 1, October 2004, pp. 5 - 24.

[AZ3] C. Frueh and A. Zakhor, "Constructing 3D City Models by Merging Ground-Based and Airborne Views" in Computer Graphics and Applications, November/December 2003, pp. 52 - 61.

[AZ4] C. Frueh, R. Sammon, and A. Zakhor, "Automated Texture Mapping of 3D City Models With Oblique Aerial Imagery" in 2nd International Symposium on 3D Data Processing, Visualization, and Transmission, Thessaloniki, Greece, September 2004.

[AZ5] C. Frueh, and A. Zakhor,"Capturing 2 1/2 D Depth and Texture of Time-Varying Scenes Using Structured Infrared Light", ProCAMS workshop, San Diego, CA 2005, June 2005. Also presented at 3DIM, Ottawa, Canada,June 2005 pp. 318-325.

[AZ6] C. Frueh and A. Zakhor, "Reconstructing 3D City Models by Merging Ground-Based and Airborne Views" in Proceedings of the 8th International Workshop VLBV 2003, Madrid, Spain, September 2003, pp. 306-313.

[AZ7] C. Frueh and A. Zakhor, "Automated Reconstruction of Building Façades for Virtual Walk-thrus" in SIGGRAPH Sketches and Applications, San Diego, July 2003.

[AZ8] C. Frueh and A. Zakhor, "Constructing 3D City Models by Merging Ground-Based and Airborne Views" in Conference on Computer Vision and Pattern Recognition 2003, Madison, Wisconsin, June 2003.

[AZ9] C. Frueh and A. Zakhor, "Data Processing Algorithms for Generating Textured 3D Building Façade Meshes From Laser Scans and Camera Images" in 3D Data Processing, Visualization and Transmission 2002, Padua, Italy, June 2002, p. 834-847.

[AZ10] C. Frueh and A. Zakhor, "3D model generation for cities using aerial photographs and ground level laser scans" in Computer Vision and Pattern Recognition Conference, Kauai, Hawaii, December 2001, Vol. 2, p. 31-38.

[AZ11] C. Frueh and A. Zakhor, "Fast 3D model generation in urban environments", in International Conference on Multisensor Fusion and Integration for Intelligent Systems 2001, Baden-Baden, Germany, August 2001, p. 165-170

[AZ12] J. Secord and A. Zakhor, "Tree Detection In Aerial LiDAR and Image Data", accepted by International Conference on Image Processing, Atlanta, Georgia, September 2006.

[AZ13] J. Secord and A. Zakhor "Tree Detection In Aerial LiDAR Data", presented at the Southwest Symposium on Image Analysis and Interpretation to be held in Denver, Colorado, March 2006.

Appendix I: Honors, Awards and Press Releases

- Best paper award: U. Neumann, S. You, J. Hu, B. Jiang, and J. W. Lee, “Augmented Virtual Environments (AVE): Dynamic Fusion of Imagery and 3D Models,” IEEE Virtual Reality 2003, pp. 61-67, Los Angeles California, March 2003.
- Best paper award: R. Niu, P. Varshney, M.H. Moore, and D. Klamer, “Decision Fusion in a Wireless Sensor Network with a Large Number of Sensors”, Seventh International Conference on Information Fusion, Stockholm, Sweden, June 2004.
- P. Varshney: IEEE Distinguished Lecturer for AES Society. Have lectured at Rochester, Long Island, Syracuse, Waterloo and Atlanta Sections.
- P. Varshney: Plenary lectures at National Systems Conf. in India and Passive Covert Radar Conf., 2005.
- A. Zakhor: Plenary talk at the registration workshop at CVPR 2005
- W. Ribarsky: Bank of America Endowed chair at UNC Charlotte
- June 2005, R&D magazine on the Berkeley 3D modeling system:
<http://www.rdmag.com>ShowPR.aspx?PUBCODE=014&ACCT=1400000100&ISSUE=0506&RELTYPE=PR&ORIGRELTYPE=CVS&PRODCODE=00000000&PRODLETT=H>
- May 2005 New Scientist on the Berkeley 3D modeling system:
http://www.newscientist.com/article.ns?id=mg18624985.800&feedId=online-news_rss20
- American Public Radio Interview, Future Tense, May 2005 on the Berkeley 3D modeling system: <http://tinyurl.com/dctc6>

Appendix II: Technology Transitions

- New Darpa program UrbanScape was initiated based on this Muri:
 - <http://dtsn.darpa.mil/ixo/programs.asp?id=86>
 - Program managers:
 - Dr. Tom Stratt
 - Dr. Brian Leininger
- Start up founded by post-doc supported by this Muri:
 - Dr. Christian Frueh
 - Urban-Scan: <http://www.urban-scan.com>
 - Urban-Scan subcontractor to Darpa UrbanScape through SAIC formerly GSTI-3D
- 3D city modeling project software has been submitted to Office of Technology and Licensing at Berkeley for licensing
 - Urban-Scan licensed software from UCB OTL
 - Google and Computa Labs in negotiations to license
- Two day tutorial at Berkeley to ARL personnel on operational and algorithmic aspects of 3D city modeling software
 - Provided complete video/audio/text documentation of city modeling project
- Carried out a 2 day 3D modeling of Potomac Yard Mall in Washington, DC in December 2003 for Jeff Turner of then GSTI-3D, now SAIC
- Carried out 2 day modeling of Ft. McKenna in Georgia in December 2003 in collaboration with Jeff Dehart of the ARL
 - Delivered the 3D model to Larry Tokarcik's group at ARL
- Metrolaser Inc
 - Provided 3D models for developing 3D holographic displays
 - DARPA SBIR on 3D display visualization under Tom Stratt and Brian Leininger
- Google Earth provided further funding to continue 3D modeling effort resulting from this MURI and is in the process of licensing Berkeley's 3D city modeling software
- Darpa/SRI VisBuilding project under the leadership of Dr. Ed Paranowski will utilize and extend results from this MURI.
- Sentinel AVE LLC
 - Startup with PIs from USC
 - AVE and Modeling software systems
 - Licensed from USC
 - In development with
 - Northrop Grumman – perimeter security
 - Chevron – asset security and operations
 - Raytheon - surveillance and security
 - Olympus – research lab support
- ARMY TEC
 - Lidar modeling system

- ANDRO Computational Solutions received several SBIR projects in the areas of image registration and sensor fusion for missile tracking and recognition from AFRL and Missile Defense Agency, POC Mr. A. Drozd
- Two STTR projects awarded related to MURI
 - AFOSR with JHM technolgies
 - ONR with BAE systems/Alpha Tech
- Sensis Corp. is incorporating the temporal Bayesian network model developed under this MURI in their situational awareness engine, POC Mr. A. Biss.
- Consultation and evaluation with Chubb (UTRC) on sensor fusion for security applications
- Technology transfer to Syracuse Center of Excellence on Environment and Energy Systems, sponsored by the state of NY on design of its fully instrumented headquarters building.
- Coop Research Agreement with Army Research Laboratory in the area of personnel detection based on the work on heterogeneous sensor fusion, POC Dr T. Damarla
- Air Force Office of Scientific Research Grant in the area of information fusion and information exploitation, POC Dr A. Magnus
- Office of Naval Research/Oak Ridge National Laboratory Coop Research Agreement in the area of multi-domain networks for detection of nuclear radiation and for perimeter surveillance, POC Dr. N. Rao
- Presented mobile situational visualization and its relation to homeland security:
 - Special session of the AAAS meeting on the National Visualization and Analytics Center, February, 2005, at AppliedVis 2005, May, 2005
 - DHS Regional Visualization and Analytics Centers, January, 2006
- Spun off a new ARO funded project on eye point dependent models applied to terrain analysis:
 - Based on urban terrain analysis in this MURI.
- Established the Southeastern Regional Visualization and Analytics Center, funded by DHS:
 - critical infrastructure simulations for disaster relief planning and emergency response.
 - Will use terrain visualization and modeling capabilities developed in MURI.
- Bank of America anti-money-laundering project
 - Bank activity visualization on geo-political structure
- Sarnoff: Collaboration on uncertainty visualization and probabilistic moving targets
- NASA AMES: Collaboration on multimodal situational visualization and software development
- Raytheon: Transition software on low uncertainty compression/registration algorithms for terrain.

Appendix III: Personnel

Principal Investigators

Avideh Zakhori, (UC Berkeley)
Bill Ribarsky, (UNC Charlotte)
Ulrich Neumann (USC)
Pramod Varshney (Syracuse)
Suresh Lodha (UC Santa Cruz)

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Dr. Suya You, Postdoc
Dr. Ruixin Niu, Postdoc
Russell Sammon, Staff engineer

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Xin Zhang
Justin Jang
Tazama St. Julien
David Krum
Lu Wang, PhD
Jinhui Hu, PhD
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Bolan Jiang, PhD
Jun Park, PhD
Tat Leung Chung, MS
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Jie Yang, MS
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Vidhya Jayakrishnan, MS
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Edward Kreps, MS
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Jose Renteria, PhD

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Lilly Spirkovska, PhD
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Karthik-Kumar Arun-Kumar, MS
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Oliver Wang
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Michael Shafae
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Christopher Campbell
James Davis
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Arthur Keller
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Weidong Shi
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Andrew Ames, BS

Adam Bickett, BS

Jason Bane, BS

Nikolai M. Faaland, BS

Appendix IV: Publications

BOOKS (Total: 2)

1. G.L. Foresti, C.S. Regazzoni and P.K. Varshney (Eds.), *Multisensor Surveillance System: The Fusion Perspective*, Kluwer Academic Press, 2003.
2. "Illuminating the Path", Research Agenda for visualization and analytics program, 2005, Thomas and Cook.

BOOK CHAPTERS (Total: 4)

1. Peter Sturm, Sri Kumar Ramalingam, and Suresh K. Lodha, "On Calibration, Structure from Motion and Multi-View Geometry for Generic Camera Models", in Imaging Beyond the Pin-hole Model, K. Daniilidis, R. Klette, and A. Leonardis (editors), Kluwer Academic Publishers, 2005.
2. William Ribarsky. Virtual Geographic Information Systems. The Visualization Handbook, Charles Hanson and Christopher Johnson, editors (Academic Press, New York, 2003).
3. Development of Tools for Construction of Urban Databases and Their Efficient Visualization," Nickolas Faust and William Ribarsky, Modeling and Visualizing the Digital Earth, Mahdi Abdelguerfi, Editor (Kluwer, Amsterdam, 2001).
4. William Ribarsky, Nickolas Faust, Zachary Wartell, Christopher Shaw, and Justin Jang, "Visual Query of Time-Dependent 3D Weather in a Global Geospatial Environment," Mining Spatio-Temporal Information Systems, R. Ladner, K. Shaw, and Mahdi Abdelguerfi, Editors (Kluwer, Amsterdam, 2002).

PEER-REVIEWED JOURNALS (Total: 35)

1. Secord and A. Zakhor, Tree Detection in Urban Regions Using Aerial LiDAR and Image Data, IEEE Geoscience and Remote Sensing Letters (GRSL), Vol. 4, No. 2, pp. 196-200, April 2007.
2. C. Frueh, S. Jain, and A. Zakhor, "Data Processing Algorithms for Generating Textured 3D Building Facade Meshes from Laser Scans and Camera Images", International Journal of Computer Vision, 61 (2), pp. 159-184, February 2005.
3. Frueh and A. Zakhor, "An Automated Method for Large-Scale, Ground-Based City Model Acquisition", International Journal of Computer Vision, 60 (1), pp. 5-24, October 2004
4. Frueh and A. Zakhor, "Constructing 3D City Models by Merging Ground-Based and Airborne Views", IEEE Computer Graphics and Applications, Special Issue Nov/Dec 2003.
5. Justin Jang, Peter Wonka, William Ribarsky, and C.D. Shaw. "Punctuated Simplification of Man-Made Objects," The Visual Computer, Vol 22(2), pp 136-145 (2006).
6. William Ribarsky, co-editor, Special Issue on Haptics, Telepresence, and Virtual Reality, IEEE Transactions on Visualization and Computer Graphics (November, 2005).
7. William Ribarsky, co-editor. Special Issue on Haptics, Virtual and Augmented Reality, IEEE Transactions on Visualization and Computer Graphics (November, 2005).

8. William Ribarsky, chapter editor, "The Science of Analytic Reasoning". Illuminating the Path: Research and Development Agenda for Visual Analytics, James Thomas and Kristin Cook, editors. IEEE Computer Society Press (May, 2005).
9. Remco Chang, Thomas Butkiewicz, Caroline Ziemkiewicz, Zachary Wartell, Nancy Pollard, and William Ribarsky. Hierarchical Simplification of City Models to Maintain Urban Legibility. Submitted to IEEE Transactions on Visualization and Computer Graphics.
10. William Ribarsky. Virtual Geographic Information Systems. The Visualization Handbook, pp. 435-463 (Academic Press, New York, 2004).
11. William Ribarsky, editor (with Holly Rushmeier). 3D Reconstruction and Visualization of Large Scale Environments. Special Issue of IEEE Computer Graphics & Applications (December, 2003).
12. Zachary Wartell, Larry Hodges, and William Ribarsky, "A Geometric Comparison of Algorithms for Fusion Control in Stereoscopic HTDs," Report GIT-GVU-00-09, pp. 129-143, IEEE Transactions on Visualization and Computer Graphics (2002).
13. Tony Wasilewski, William Ribarsky, and Nickolas Faust. From Urban Terrain Models to Visible Cities. Vol. 22(4), pp. 10-15, *IEEE CG&A* (2002).
14. Eduard Groeller, William Ribarsky, and Helwig Loeffelmannm, Editors, Computers & Graphics, Special Issue on Data Visualization (Vol. 24, no. 3, June, 2000).
15. Bastian Leibe, Thad Starner, Zachary Wartell, William Ribarsky, Larry Hodges, Justin Weeks, Brad Singletary, and David Krum, "Towards Spontaneous Interaction with the Perceptive Workbench, A Semi-Immersive Virtual Environment," IEEE Computer Graphics & Applications, pp. 54-65, (2000).
16. Q. Zhang and P. K. Varshney, "Decentralized M-ary Detection via Hierarchical Binary Decision Fusion", *Information Fusion*, vol 2, pp 3-16, March 2001.
17. Q. Zhang, P.K. Varshney and R.D.Wesel, "Optimal Bi-level Quantization of i.i.d. Sensor Observations for Binary Hypothesis Testing", *IEEE Trans. on Information Theory*, vol 48, pp 2105-2111, July 2002.
18. Nojeong Heo and Pramod K. Varshney, "Energy-Efficient Deployment of Intelligent Mobile Sensor Networks," *IEEE Trans. on Systems, Man, and Cybernetics, PART A*, vol. 35, no. 1, pp.78-92, January 2005.
19. H. Chen, S. Lee, R. M. Rao, M. A. Slamani and P. K. Varshney, "Imaging for Concealed Weapon Detection," *IEEE Signal Processing Magazine*, vol.22, no. 2, pp.52-61, March 2005
20. R. Niu, P. Varshney, K. Mehrotra and C. Mohan, "Temporally Staggered Sensors in Multi-Sensor Target Tracking Systems," *IEEE Transactions on Aerospace and Electronic Systems*, pp 794-808, July 2005
21. Qi Cheng, Pramod K. Varshney, Kishan G. Mehrotra and Chilukuri K. Mohan, "Bandwidth Management in Distributed Sequential Detection," *IEEE Trans. Inform. Theory*, Vol. 51, No. 8, pp. 2954-2961, Aug. 2005
22. R. Niu and P. Varshney, "Distributed Detection and Fusion in a Large Wireless Sensor Network of Random Size," *EURASIP Journal on Wireless Communications and Networking*, pp 462-472, September 2005.
23. E. Elbasi, L. Zuo, K.G.Mehrotra, C. Mohan and P.K. Varshney, "Control Charts Approach for Scenario Recognition in Video Sequences", *Turkish Journal of Electrical Engineering & Computer Sciences*, Volume 13, Issue 3, pp. 303-310, 2005.

24. Ramesh Rajagopalan, Kishan Mehrotra, Chilukuri K Mohan, and Pramod K Varshney, "Hierarchical Dynamic Personnel Movement Planning for Risk Minimization in Hazardous Environments", IEEE Transactions on Aerospace and Electronic Systems, to appear.
25. R. Niu and P. Varshney, "Target Location Estimation in Sensor Networks with Quantized Data," IEEE Transactions on Signal Processing, pp 4519-4528, December 2006.
26. Chilukuri K. Mohan, Kishan G. Mehrotra, Pramod K. Varshney and Jie Yang, "Temporal Uncertainty Reasoning Networks for Evidence Fusion with Applications to Object Detection and Tracking," International Journal of Information Fusion, (to appear)
27. R. Niu, B. Chen, P. Varshney, "Fusion of Decisions Transmitted over Rayleigh Fading Channels in Wireless Sensor Networks", IEEE Transactions on Signal Processing, pp 1018-1027, March 2006.
28. R. Niu, P. Varshney, and Q. Cheng, "Distributed Detection in a Wireless Sensor Network with a Large Number of Sensors", International Journal on Information Fusion, Vol. 7, No. 4, pp 380-394, December 2006.
29. Lilly Spirkovska and Suresh K. Lodha, ``Context-aware intelligent assistant approach for decreasing pilot workload", Journal of Aerospace Computing, Information, and Communication, September 2005, Vol. 2. No. 9, pages 386--400.
30. Suresh K. Lodha, Nikolai M. Faaland, and Jose Renteria, "Hierarchical Toplogy Preserving Compression of 3D Vector Fields using Bintree and Triangular Quadtrees", IEEE Transactions on Visualization and Computer Graphics, Vol. 9, No. 4, October 2003, pages 433—442
31. Suresh K. Lodha, Krishna M. Roskin, and Jose C. Renteria, ``Hierarchical Topology Preserving Compression of Terrains", Visual Computer, September 2003.
32. Lilly Spirkovska and Suresh K. Lodha, ``AWE: Aviation Weather Data Visualization Environment", Computers and Graphics, Volume 26, No.~1, February 2002, pp.~169--191. NASA/TM-2000-209617, December 2000.
33. J. Hu, S. You, and U. Neumann, "Texture Painting from Video," the Journal of WSCG, Jan 2005.
34. U. Neumann, S. You, J. Hu, B. Jiang, and I. O. Sebe, "Visualizing Reality in an Augmented Virtual Environment," Presence:Teleoperators and Virtual Environments Journal, Vol 13, No. 2, MIT press, pp. 222-233, April 2004.
35. J. Hu, S. You, U. Neumann, "Approaches to Large-Scale Urban Modeling, "IEEE Computer Graphics and Applications, Vol. 23, No. 6, pp. 62-69, November 2003.

CONFERENCE (Total: 111)

1. V. Markov, S. A. Kupiec, and A. Zakhor, "Autostereoscopic Displays for Visualization of Urban Environments", Proceedings of SPIE Vol. 6392 (Boston 2006) Three-Dimensional TV, Video, and Display V.
2. J. Secord and A. Zakhor, "Tree Detection In Aerial LiDAR and Image Data", International Conference on Image Processing, Atlanta, Georgia, September 2006.
3. Lakhia, "Efficient Interactive Rendering of Detailed Models with Hierarchical Levels of Detail" in *2nd International Symposium on 3D Data Processing, Visualization, and Transmission*, Thessaloniki, Greece, September 2004, pp 275-282.

4. Frueh, R. Sammon, and A. Zakhori, "Automated Texture Mapping of 3D City Models With Oblique Aerial Imagery", in 2nd International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT), Thessaloniki, Greece 2004.
5. C. Frueh and A. Zakhori, "*Constructing 3D City Models by Merging Ground-Based and Airborne Views*", in IEEE Conference on Computer Vision and Pattern Recognition 2003, Madison, USA, June 2003, p. II-562 - 69.
6. C. Früh and A. Zakhori, "Automated Reconstruction of Building Façades for Virtual Walk-thrus", SIGGRAPH 2003, Sketches and Applications, San Diego, 2003
7. C. Früh and A. Zakhori, "Reconstructing 3D City Models by Merging Ground-Based and Airborne Views", Proc. of 8th International Workshop on Visual Content Processing and Representation, Madrid, 2003, p. 306-313
8. C. Frueh and A. Zakhori, "*Data Processing Algorithms for Generating Textured 3D Building Façade Meshes From Laser Scans and Camera Images*", in Proc. 3D Data Processing, Visualization and Transmission 2002, Padua, Italy, June 2002, p. 834 - 847
9. C. Frueh and A. Zakhori, "*3D Model Generation for Cities Using Aerial Photographs and Ground Level Laser Scans*", in IEEE Conference on Computer Vision and Pattern Recognition Conference, Kauai, USA, December 2001, p. II-31-38, vol.2. 2.
10. C. Früh and A. Zakhori, "Fast 3D Model Generation In Urban Environments", IEEE Conference on Multisensor Fusion and Integration for Intelligent Systems 2001, Baden-Baden, Germany, August 2001, p. 165-170.
11. Xin Zhang, Tazama Upendo St Julien, Ramesh Rajagopalan, William Ribarsky, Pramod Varshney, Chilukuri Mohan, and Kishan Mehrotra . Dynamic Decision Support for Mobile Situational Visualization. AppliedVis 2005.
12. Tazama St. Julien, Joseph Scoccinaro, Jonathan Gdalevich, and William Ribarsky. Sharing of Precise 4D Annotations in Collaborative Mobile Situational Visualization. Submitted to *IEEE Symposium on Wearable Computing*.
13. Remco Chang, Thomas Butkiewicz, Caroline Ziemkiewicz, Zachary Wartell, Nancy Pollard, and William Ribarsky. Using Urban Legibility to Produce Completely Navigable Large Scale Urban Models. To be published, *ACM SIGGRAPH 2006 Short Papers*.
14. Ernst Houtgast, Onno Pfeiffer, Zachary Wartell, William Ribarsky, and Frits Post. Navigation and Interaction in a Multi-Scale Stereoscopic Environment. *IEEE Virtual Reality 2004*.
15. Nickolas Faust and William Ribarsky. Integration of GIS, Remote Sensing, and Visualization. Invited paper, Proc. Remote Sensing 2003 (Barcelona, 2003).
16. David Krum, Olugbenga Omoteso, William Ribarsky, Thad Starner, and Larry Hodges. Evaluation of a Multimodal Interface for 3D Terrain Visualization. pp. 411-418 *IEEE Visualization 2002*.
17. Justin Jang, William Ribarsky, Christopher Shaw, and Peter Wonka. Appearance-Preserving View-Dependent Visualization. *IEEE Visualization 2003*, pp. 473-480.
18. William Ribarsky, Zachary Wartell, and Nickolas Faust. Precision Markup Modeling and Display in a Global Geospatial Environment. *Proceedings SPIE 17th International Conference on Aerospace/Defense Sensing, Simulation, and Controls* (2003).

19. Benjamin Watson, Neff Walker, Peter Woytiuk, and William Ribarsky Maintaining Usability During 3D Placement Despite Delay. *IEEE Virtual Reality 2003*, pp. 133-140 (2003).
20. Zachary Wartell, Eunjung Kang, Tony Wasilewski, William Ribarsky, and Nickolas Faust. Rendering Vector Data over Global, Multiresolution 3D Terrain. *Eurographics-IEEE Visualization Symposium 2003*, pp. 213-222.
21. Peter Wonka, Michael Wimmer, Francois Sillion, and William Ribarsky. Instant Architecture. *Siggraph 2003*, pp. 669-678 (2003).
22. David Krum, Rob Melby, William Ribarsky, and Larry Hodges. Isometric Pointer Interfaces for Wearable 3D Visualization. *ACM CHI 2003*.
23. William Ribarsky, Justin Jang, Chris Shaw, and Nickolas Faust. View-Dependent Multiresolution Splatting of Non-Uniform Data. pp. 125-132, *Eurographics-IEEE Visualization Symposium 2002*.
24. William Ribarsky, "Multiresolution Visualization of Urban Environments," *Intersection of Geospatial Information and Information Technology* (National Academy of Sciences, 2002).
25. William Ribarsky, "Towards the Visual Earth," *Workshop on Intersection of Geospatial Information and Information Technology*, National Research Council (October, 2001).
26. William Ribarsky, Christopher Shaw, Zachary Wartell, and Nickolas Faust, "Building the Visual Earth," to be published, *SPIE 16th International Conference on Aerospace/Defense Sensing, Simulation, and Controls* (2002).
27. David Krum, William Ribarsky, Chris Shaw, Larry Hodges, and Nickolas Faust, "Situational Visualization," pp. 143-150, *ACM VRST 2001* (2001).
28. David Krum, Olugbenga Omoteso, William Ribarsky, Thad Starner, and Larry Hodges, "Speech and Gesture Multimodal Control of a Whole Earth 3D Virtual Environment," *Eurographics-IEEE Visualization Symposium 2002. Winner of SAIC Best Student Paper award*.
29. William Ribarsky, T.Y. Jiang, Tony Wasilewski, Nickolas Faust, Brendan Hannigan, and Mitchell Parry, "Acquisition and Display of Real-Time Atmospheric Data on Terrain," *Proceedings of the Eurographics-IEEE Visualization Symposium 2001*, pp. 15-24.
30. Zachary Wartell, Larry Hodges, and William Ribarsky, "Characterizing Image Fusion Techniques in Stereoscopic Displays," pp. 223-232, *Graphics Interface 2001* (2001).
31. Christopher D. Shaw, R. Mitchell Parry, Beth Plale, Frank T. Jiang, Anthony A. Wasilewski, William Ribarsky, and Nickolas L. Faust, "Real-Time Weather Data on Terrain," *SPIE Aerosense 2001*, Vol. 4368A, pp. 1-8.
32. Nick Faust, William Ribarsky, and Frank Jiang, "Client-Server Modes of GTVGIS," Vol. 4368A, *SPIE 15th Annual Conference on Aerosense* (2001).
33. Mitchell Parry, Brendan Hannigan, William Ribarsky, T.Y. Jiang, and Nickolas Faust, "Hierarchical Storage and Visualization of Real-Time 3D Data," *Proc. SPIE 15th Annual Conference on Aerosense 2001*, Vol. 4368A.
34. Matthew Grimes, Tony Wasilewski, Nickolas Faust, and William Ribarsky, "Semiautomatic Landscape Feature Extraction and Modeling," *Proc. SPIE 15th Annual Conference on Aerosense 2001*, Vol. 4368A.

35. A.F. Seay, D. Krum, L. Hodges, and W. Ribarsky. Simulator Sickness and Presence in a High FOV Virtual Environment. Proc. IEEE Virtual Reality 2001, pp. 299-300 (2001).
36. Bastian Leibe, Thad Starner, William Ribarsky, David Krum, Larry Hodges, and Zachary Wartell. “The Perceptive Workbench Towards Spontaneous and Natural Interaction in Semi-Immersive Virtual Environments,” pp. 13-20, IEEE Virtual Reality 2000. *Won the IEEE Virtual Reality 2000 best paper award.*
37. William Ribarsky, Nickolas Faust, William Ribarsky, T.Y. Jiang, and Tony Wasilewski, “Real-Time Global Data Model for the Digital Earth,” Proceedings of the INTERNATIONAL CONFERENCE ON DISCRETE GLOBAL GRIDS (2000).
38. A. Fleming Seay, David Krum, Larry Hodges, and William Ribarsky, “Direct Manipulation on the Virtual Workbench: Two Hands Aren’t Always Better Than One,” Report GIT-GVU-00-07, Presence. *Winner of SAIC 2000 award for best graduate student research papers.*
39. C. K. Mohan, K. G. Mehrotra, and P. K. Varshney, “Temporal Update Mechanisms for Decision Making with Aging Observations in Probabilistic Networks,” Proc. AAAI Fall Symposium, Cape Cod, MA, Nov. 2001.
40. R. Niu, P. K. Varshney, K. G. Mehrotra and C. K. Mohan, “Temporal Fusion in Multi-Sensor Target Tracking Systems,” in Proceedings of the Fifth International Conference on Information Fusion, July 2002, Annapolis, Maryland.
41. Suresh K. Lodha, Nikolai M. Faaland, Amin P. Charaniya, Pramod Varshney, Kishan Mehrotra, and Chilukuri Mohan, “Uncertainty Visualization of Probabilistic Particle Movement,” in the Proceedings of The IASTED Conference on Computer Graphics and Imaging”, August 2002.
42. Q. Cheng, P. K. Varshney, K. G. Mehrotra and C. K. Mohan, “Optimal Bandwidth Assignment for Distributed Sequential Detection,” in Proceedings of the Fifth International Conference on Information Fusion, July 2002, Annapolis, Maryland.
43. C. Mohan, K. Mehrotra, and P. Varshney,” Temporal Uncertainty Processing,” Fusion'02 Workshop, Utica (NY), July 2002.
44. Ramesh Rajagopalan, Chilukuri K. Mohan, Kishan G. Mehrotra and Pramod K. Varshney, “Evolutionary multi-objective crowding algorithm for path computations,” Proc. fifth international conference on knowledge based computer systems, Hyderabad, India, December 2004.
45. R. Niu and P.K.Varshney, “Target Location Estimation in Wireless Sensor Networks Using Binary Data,” Proceedings of the 38th Annual Conference on Information Sciences and Systems, Princeton, NJ, March 2004
46. Ramesh Rajagopalan, Pramod K. Varshney, Chilukuri K. Mohan and Kishan G. Mehrotra, “Sensor Placement for Energy Efficient Target Detection in Wireless Sensor Networks: A multi-objective Optimization Approach,” Proc. of the39th Annual Conference on Information Sciences and Systems, Baltimore, Maryland, March 2005.
47. D. Devicharan, K. Mehrotra, P.K. Varshney, C.K. Mohan, L. Zuo, “Scenario Recognition with Audio-Visual Sensor Fusion,” Proc. of the SPIE Defense and Security Symposium, Orlando, FL, March 2005.

48. Ramesh Rajagopalan, Chilukuri K. Mohan, Pramod K. Varshney and Kishan Mehrotra, "Multi-objective mobile agent routing in wireless sensor networks," Proc. of the IEEE Congress on Evolutionary Computation, Edinburgh, Scotland, April 2005
49. E. Elbasi, L. Zuo, K. Mehrotra, C.K. Mohan and P. Varshney, "Control Charts Approach for Scenario Recognition," Proc. Turkish Artificial Intelligence and Neural Networks Symp., June 2004.
50. Ramesh Rajagopalan, Chilukuri K. Mohan, Kishan Mehrotra and Pramod K Varshney, "An Evolutionary Multi-objective Crowding Algorithm (EMOCA): Benchmark Test Function Results," 2nd Indian International Conference on Artificial Intelligence, Pune, India, December 2005.
51. P. K. Varshney and I. L. Coman, "Distributed Multi-Sensor Surveillance: Issues and Recent Advances", Proc. 2nd European Workshop on Advanced Video-Based Surveillance systems, Kingston, UK, Sept. 2001.
52. Q. Cheng, P. Varshney, K. Mehrotra and C. Mohan, "Optimal Bandwidth Assignment for Distributed Sequential Detection", Proceedings of the Fifth International Conference on Information Fusion, July 2002, Annapolis, Maryland.
53. C. Regazzoni and P.K Varshney, "Multisensor Surveillance Systems Based on Image and Video Data", Proc. of the IEEE Conf. on Image Proc., Rochester, NY, Sept. 2002.
54. J. Yang, C. Mohan, K. Mehrotra and P. Varshney , "A Tool for Belief Updating over Time in Bayesian Networks" , in Proc. 5th Int. Conf. on Tools for A.I., Washington (D.C.), Nov. 2002, pp.284-289.
55. N. Heo and P. K. Varshney, "A Distributed Self Spreading Algorithm for Mobile Wireless Sensor Networks," Proc. of IEEE Wireless Communications and Networking Conference, WCNC 2003, March 2003.
56. R. Niu, P. Varshney, K. Mehrotra and C. Mohan, ``Sensor Staggering in Multi-Sensor Target Tracking Systems", Proceedings of the 2003 IEEE Radar Conference, Huntsville AL, May 2003
57. L. Snidaro, R. Niu, P. Varshney, and G.L. Foresti, ``Automatic Camera Selection and Fusion for Outdoor Surveillance under Changing Weather Conditions", Proceedings of the 2003 IEEE International Conference on Advanced Video and Signal Based Surveillance, Miami FL, July 2003
58. R. M. Rao, H.Chen, M. A. Slamani, and P. K. Varshney, "Imaging for Concealed Weapon Detection", International Conference on Advanced Technologies for Homeland Security, Sept. 25-26, 2003, University of Connecticut, Storrs, Connecticut.
59. N. Heo and P. K. Varshney, "An Intelligent Deployment and Clustering Algorithm for a Distributed Mobile Sensor Network," Proc. of the 2003 IEEE International Conference on Systems, Man & Cybernetics, Oct. 2003
60. R.Niu and P.K.Varshney, "Target Location Estimation in Wireless Sensor Networks Using Binary Data," Proceedings of the 38th Annual Conference on Information Sciences and Systems, Princeton, NJ, March 2004
61. R. Niu and P. Varshney, "Sampling Schemes for Sequential Detection in Colored Noise", Proc. of the 2004 IEEE International Conference on Acoustics, Speech, and Signal Processing, Montreal, Canada, May 2004.

62. L. Snidaro, R. Niu, P. Varshney, and G.L. Foresti, ``Sensor Fusion for Video Surveillance'', Proceedings of the Seventh International Conference on Information Fusion, Stockholm, Sweden, June 2004
63. R. Niu, P. Varshney, M.H. Moore, and D. Klamer, ``Decision Fusion in a Wireless Sensor Network with a Large Number of Sensors'', Proceedings of the Seventh International Conference on Information Fusion, Stockholm, Sweden, June 2004.
64. M. Xu, R. Niu, and P. Varshney, "Detection and Tracking of Moving Objects in Image Sequences with Varying Illumination", Proceedings of the 2004 IEEE International Conference on Image Processing, Singapore, October 2004.
65. P. K. Varshney, H. Chen and R.M. Rao, "On signal/image processing for concealed weapons detection from stand-off range," Invited paper, Proc. of the SPIE defense & Security symposium, pp. 93-97, March 29-31, 2005, Orlando, Florida USA
66. Xin Zhang, Tazama Upendo St Julien, Ramesh Rajagopalan, William Ribarsky, Pramod Varshney, Chilukuri K Mohan and Kishan Mehrotra, "An integrated path engine for mobile situational visualization," Applied Vis Conference, Asheville, NC, April 2005.
67. R. Niu and P. Varshney, "Decision Fusion in a Wireless Sensor Network with a Random Number of Sensors," Proceedings of the 2005 IEEE International Conference on Acoustics, Speech, and Signal Processing, Philadelphia, PA, March 2005.
68. Ramesh Rajagopalan, Chilukuri K. Mohan, Pramod K. Varshney and Kishan Mehrotra, "Multi-objective mobile agent routing in wireless sensor networks," Proc. of the IEEE Congress on Evolutionary Computation, Edinburgh, Scotland, April 2005.
69. Ramesh Rajagopalan, Pramod K. Varshney, Kishan G. Mehrotra and Chilukuri K. Mohan, "Fault tolerant mobile agent routing in sensor networks: A multi-objective optimization approach," Proc. of the 2nd IEEE Upstate NY workshop on Comm. and Networking, Rochester, NY, November 2005.
70. Suresh K. Lodha, Darren Fitzpatrick, and David P. Helmbold, "Aerial Lidar Data Classification using AdaBoost", Manuscript, 2006.
71. Oliver Wang, Suresh Lodha, and David P. Helmbold, "A Bayesian Approach to Building Footprint Extraction from Aerial Lidar Data", To appear in Proceedings of 3DPVT Conference, 2006.
72. Oliver Wang and Suresh K. Lodha, "Automatic Segmentation of Buildings from Pre-Classified Aerial Lidar Data", Manuscript, 2006.
73. Srikumar Ramalingam, Suresh K. Lodha, and Peter Sturm, "A Generic Structure-from-Motion Framework", submitted to Computer Vision and Image Understanding, January 2005.
74. Suresh K. Lodha, Darren M. Fitzpatrick, and David P. Helmbold, "Aerial Lidar Data Classification using Expectation-Maximization," Proceedings of the SPIE Conference on Vision Geometry XIV, Vol. 6499, pp.~L1--L11, San Jose, CA, January 2007.
75. Suresh K. Lodha, Edward J. Kreps, David P. Helmbold, Darren Fitzpatrick, "Aerial Lidar Data Classification using Support Vector Machines (SVM)," Proceedings of the Conference on 3DPVT (3D Data Processing, Visualization, and Transmission), Chapel Hill, North Carolina, June 2006.

76. Kartik Venkatraman, Suresh K. Lodha, and Raghu Raghavan, ``A Kinematic-Variational Formulation for Animating Skin with Wrinkles'', Computers and Graphics, Volume 29, No. 5, October 2005, pp.~756--770.
77. Suresh K. Lodha and Yongqin Xiao, "GSIFT: Geometric Scale Invariant Feature Transform for Data Registration", Proceedings of the SPIE Conference on Vision Geometry XIV, Vol. 6066, pp.~L1--L11, San Jose, CA, January 2006.
78. Srikumar Ramalingam, Peter Sturm and Suresh K. Lodha, Theory and Calibration for Axial Cameras, Proceedings of the Asian Conference on Computer Vision (ACCV), Hyderabad, India, January 2006.
79. Yongqin Xiao and Suresh K. Lodha, "Geometrically Invariant Feature Descriptors for Height Data Registration", Proceedings of the IVCNZ (Image and Vision Computing) Conference, pp.~229--234, Dunedin, New Zealand, November 2005.
80. Srikumar Ramalingam, Peter Sturm, and Suresh K. Lodha, "Towards Generic Self-Calibration of Cnetral Cameras", Proceedings of Omnidiviz workshop in ICCV, Beijing, China, October 2005.
81. Peter Sturm, Srikumar Ramalingam, and Suresh K. Lodha, "On Calibration, Structure-from-Motion and Multi-View Geometry for Panoramic Imaging Models", Proceedings of the 2nd ISPRS Panoramic Photogrammetry Workshop, Berlin, Germany, 2005.
82. Srikumar Ramalingam, Peter Sturm, and Suresh K. Lodha, "Towards Complete Generic Camera Calibration", Proceeedings of Computer Vision and Pattern Recognition (CVPR), San Diego, CA, June 2005, Vol. 1, pages 1093--1098.
83. Karthik-Kumar Arun-Kumar and Suresh K. Lodha, ``Semi-Automatic Roof Reconstruction from Aerial Lidar Data using K-Means with Refined Seeding'', Proceedings of the ASPRS (American Society for Photogrammetry and Remote Sensing) Conference, Baltimore, Maryland, March 2005.
84. Suresh K. Lodha, Andrew Ames, Adam Bickett, Jason Bane, and Hemanth Singamsetty, ``3D Geospatial Visualization of UCSC Campus'', Proceedings of the ASPRS (American Society for Photogrammetry and Remote Sensing) Conference, Baltimore, Maryland, March 2005.
85. Sanjit Jhala and Suresh K. Lodha, "Stereo and Lidar-Based Pose Estimation with Uncertainty for 3D Reconstruction", Proceedings of Vision, Modeling, and Visualization Conference, Stanford, Palo Alto, CA, November 2004.
86. Srikumar Ramalingam, Suresh K. Lodha, and Peter Sturm, "Srikumar Ramalingam, Suresh K. Lodha, and Peter Sturm, ``A Generic Structure-from-Motion Algorithm for Cross-Camera Scenarios'', Proceedings of the OmniVis (Omnidirectional Vision, Camera Networks, and Non-Classical Cameras) Conference, Prague, Czech Republic, May 2004.
87. Amin Charaniya, Roberto Manduchi, and Suresh K. Lodha, "Supervised Parametric Classification of Aerial Lidar Data", Proceedings of the IEEE workshop on Real-Time Sensors and Their Use, Washington DC, June 2004.
88. Hemanth Singamsetty and Suresh K. Lodha, "An Integrated Geospatial Data Acquisition System for Reconstructing 3D Environments", Proceedings of the IASTED Conference on Advances in Computer Science and Technology (ACST), St. Thomas, Virgin Islands, USA, November 2004.

89. Sanjit Jhala and Suresh K. Lodha, "On-line Learning of Motion Patterns using an Expert Learning Framework," Proceedings of the IEEE workshop on Learning in Computer Vision and Pattern Recognition, Washington DC, June 2004.
90. Christopher Campbell, Michael M. Shafae, Suresh K. Lodha, and Dominic W. Massaro, "Discriminating Visible Speech Tokens using Multi-Modality", Proceedings of the International Conference on Auditory Display (ICAD), Boston, MA, July 2003.
91. Amin Charaniya and Suresh K. Lodha, "Speech Interface for Geo-Spatial Visualization", Proceedings for the Conference on Computer Science and Technology (CST), Cancun, Mexico, May 2003.
92. Lilly Spirkovska and Suresh Lodha, "Audio-Visual Situational Awareness for General Aviation Pilots", Proceedings of the SPIE Conference on Visualization and Data Analysis, January 2003, Vol. 5009.
93. Srikumar Ramalingam and Suresh K. Lodha, "Adaptive Enhancement of 3D Scenes using Hierarchical Registration of Texture-Mapped Models, Proceedings of 3DIM 2003, October 2003.
94. Suresh K. Lodha, Nikolai M. Faaland, Grant Wong, Amin Charaniya, Srikumar Ramalingam, and Arthur Keller, "Consistent Visualization and Querying of Geospatial Databases by a Location-Aware Mobile Agent", Proceedings of the Computer Graphics International Conference 2003, Tokyo, Japan, July 2003.
95. Amin Charaniya, Srikumar Ramalingam, Suresh Lodha, William Ribarsky, Nicholas Faust, Zach Wartell, and Tony Wasilewski, "Real-Time Uncertainty Visualization of Mobile Objects within VGIS (Virtual Geographic Information System)", poster paper and interactive demonstration at the IEEE Visualization Conference, Boston , MA, October 2002.
96. Srikumar Ramalingam, Nikolai Faaland, Amin Charaniya and Suresh Lodha, "Visualization of Heterogeneous Geo-Spatial Intelligence in a Mobile Environment", interactive demonstration at the IEEE Visualization Conference, Boston, MA, October 2002.
97. Suresh K. Lodha, Nikolai M. Faaland, Amin P. Charaniya, Pramod Varshney, Kishan Mehrotra, and Chilukuri Mohan, "Uncertainty Visualization of Probabilistic Particle Movement", Proceedings of The IASTED Conference on ^KComputer Graphics and Imaging", August 2002, pages 226-232.
98. Suresh Lodha, A. P. Charaniya, Nikolai M. Faaland, and Srikumar Ramalingam, "Visualization of Spatio-Temporal GPS Uncertainty within a GIS Environment" Proceedings of SPIE Conference on Aerospace/Defense Sensing, Simulation, and Controls, April 2002.
99. Suresh K. Lodha, Ellen Venable, David Marsh, Doanna Meads, Nguyet Manh, Casey Robinson and Krishna Roskin, "Use of Natural Sounds and Metaphors for Data Perceptualization," Proceedings of the SPIE Conference on Visual Data Exploration and Analysis VIII, San Jose, CA, January, 2001, Volume 4302, pages 180--190.
100. Suresh K. Lodha, Nikolai M. Faaland, Grant Wong, Amin Charaniya, Srikumar Ramalingam, and Arthur Keller, "Consistent Visualization and Querying of Geospatial Databases by a Location-Aware Mobile Agent", ACM GIS Conference, November 2002.

101. S.Lodha, N.Faaland, A.Charaniya, P.Varshney, K.Mehrotra and C.Mohan. *Visualization of Uncertain particle movement*. Proceedings of the Computer Graphics and Imaging Conference, pages 226-232, 2001.
102. Suresh K. Lodha and Arvind Varma, "Spatio-Temporal Visualization of Urban Crimes on a GIS Grid," Proceedings of the ACM GIS Conference, November 2000, ACM Press, pages 174--179.
103. Suresh K. Lodha, Jose Renteria and Krishna M. Roskin, "Topology Preserving Compression of 2D Vector Fields," Proceedings of IEEE Visualization '2000, October 2000, pp. 343--350.
104. I.O. Sebe, S. You, and U. Neumann, "Rapid Part-Based 3D Modeling," Proc. of ACM Symposium on Virtual Reality Software and Technology (VRST), Nov 2005, Monterey, CA, pp.143-146.
105. I.O. Sebe, S. You, and U. Neumann, "Globally Optimum Multiple Object Tracking," SPIE Defense and Security Symposium 05. Acquisition, Tracking, and Pointing XIX conference. March 2005, Orlando, FL, Volume 5810, pp.82-93.
106. I.O. Sebe, S. You, U. Neumann, "Dynamic Objects Modeling and 3D Visualization," ASPRS04, May 2004, Colorado.
107. B. Jiang, S. You, U. Neumann, "A Robust Tracking System for Outdoor Augmented Reality," IEEE Virtual Reality 2004, Chicago, March 27-31, 2004. pp. 3 - 10.
108. J. Hu, S. You, U. Neumann, "Building Modeling from LiDAR and Aerial Imagery," in the proceeding of ASPRS, May 2004.
109. I. O. Sebe, J. Hu, S. You, U. Neumann, " 3D Video Surveillance with Augmented Virtual Environments," ACM SIGMM 2003 Workshop on Video Surveillance, pp 107-112, Berkeley, California, (in conjunction with ACM Multimedia 2003), November 2003, Berkeley, CA, pp.107-112
110. S. You, J. Hu, U. Neumann, and P. Fox, "Urban Site Modeling From LiDAR," Lecture Notes in Computer Science Series, Springer-Verlag, Vol. 2669, ISSN 0302-9743, G. Goos, J. Hartmanis, and J.Van Leeuwen (Eds.): Proceedings of Second International Workshop on Computer Graphics and Geometric Modeling, Vol. 2668, pp. 579 - 588, Montreal, CANADA, May 2003.
111. U. Neumann, S. You, J. Hu, B. Jiang, and J. W. Lee, "Augmented Virtual Environments (AVE): Dynamic Fusion of Imagery and 3D Models," IEEE Virtual Reality 2003, pp. 61-67, Los Angeles California, March 2003.